Crop Recommendation & Yield Prediction System-A Review

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Abstract— Agriculture supports world economies and food safety, but factors such as soil infertility, inefficient resource utilization, and climatic fluctuations remain on-going effects on productivity. Crops must be chosen carefully, taking into account the soil type and the region; this choice affects both optimizing yield and implementing sustainable farming practices.Conventional methods typically rely on experience-based intuition, which occasionally may not produce the best outcomes.By recommending suitable crops based on soil type and location, a machine learning technology can assist farmers. Instead than concentrating solely on the amount of moisture in the soil, this method considers the soil's overall characteristics as well as location-related elements to provide accurate recommendations. By examining variables such as crop name, soil type, and acreage, it can also estimate crop yield, giving farmers the ability to project production capacity before planting.

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Keywords— Crop yield optimization, crop advice, soil management, soil type, sustainable agriculture, and smart farming.

INTRODUCTION

Agriculture remains the backbone of economies worldwide, playing a vital role in providing food security, raw materials, employment, and export revenues, especially in developing nations. In today's generation, agriculture's importance has increased significantly due to growing global population, rising food demands, and pressures posed by climate conditions. As the world population is expected to surpass 9 billion by 2050, agricultural productivity must increase by nearly 70% to meet future food demands. However, traditional methods of farming are no longer sufficient to achieve this growth due to challenges like unpredictable weather patterns, soil degradation, and inefficient water usage. Modern agriculture must adopt more data-driven approaches to ensure sustainability and efficiency.

The most significant factors in deciding the right soil and crop management practices in agriculture are soil moisture and type of soil. Soil moisture determines the health of the crop and how much irrigation needs to be carried out; hence, suitable crops can be selected and growth stages evaluated. Predictions of soil moisture can be done using machine learning with advance methods of implementing historical data and current environmental condition analysis. Although predictive models may yield a mean squared error of 0.14 for one-day predictions, accuracy usually deteriorates with longer forecasts due to soil variability and environmental factors, requiring continuous improvement in modeling techniques [1].

Moisture prediction is complemented by understanding the different types of soils that provide optimal crop management for the farmers. The understanding of the different kinds of soils uniquely allows the farmers to decide what type of crops to cultivate to maximize productivity. Recently developed machine learning models have aided farmers in their pursuit. Data-driven methodologies are applied through these models, and the output is crop suggestion based on soil classification the accuracy in these suggestions would therefore be better and more precise for the kinds of soil .This association of soil data with predictive analytics helps them take decisions and promotes the concept of sustainable agriculture practices as well [2].

1. OVERVIEW OF AI TECHNIQUES FOR SOIL AND CROP MANAGEMENT

Artificial Intelligence (AI) is revolutionizing soil and crop management, offering tools that enhance productivity, optimize resource use, and promote sustainability. By leveraging vast amounts of agricultural data, AI techniques enable precise and data-driven decisions, addressing challenges like unpredictable weather, soil degradation, and the need for higher yields. Aritificial Intelligence techniques are revolutionizing soil and crop management by providing advanced data-driven solutions that helps in optimizing the agricultural practices. AI data driven models offers valuable insights for predicting and maximize the productivity of crop based on soil type and area.

1.1. Machine Learning Algorithms

2.1.1.Supervised Learning

Supervised learning is a highly useful tool in agriculture because the nature of labeled data is much better suited for classification tasks, yield prediction, or even detection of diseases. Such tasks are very often preceded by precise predictions coming from the well-defined inputs in agriculture. For example, crop classification deals with distinguishing different types of crops using labeled spectral data. The third is yield prediction that, based on environmental input like temperature, rainfalls, and soil moisture, models such as SVM are known to perform well since they can be trained using historical information to predict yields to come.

Supervised learning is applied in applications such as disease detection. Here, the model will be trained on images or sensor data labeled as healthy or diseased. The model will, therefore learn the features of healthy and unhealthy crops that ensure early detection of diseases. Such applications are important since they facilitate timely interventions that would otherwise lead to losses. For instance, SVM was applied in crop disease detection in tomatoes [3], hence farmers could optimize their application of pest and disease control measures.

The process works by training the model with known data, such as input-output pairs, that enables it to learn patterns and consequently make correct predictions on new, unseen data. Choosing supervised learning in particular is very valuable when data can be easily labeled, such as in the case of agriculture, where visual data, sensor data, and environmental readings are considered. Such a method aids the increase in the accuracy of the predictions and also ensures that these models are reliable for real-world agricultural applications.

2.1.1.1. Support Vector Machine:

The Support Vector Machine (SVM) algorithm was utilized for crop prediction based on environmental factors like rainfall, temperature, and soil pH. Historical agricultural data were used to train the model in classifying and suggesting the most appropriate crops to be grown under certain environmental conditions[4].A linear kernel was used in the SVM model because the data set showed linear separability. The selection allowed an optimal separating boundary to be created for determining appropriate crops to be predicted. An accuracy rate of 92.6% was obtained in the trained model, proving effective in processing structured farm datasets.But when compared with the other algorithms used in this study—i.e., Decision Tree (99.87%) and k-NN (99.73%)—SVM was less accurate. It shows that though SVM is a good classifier, there could be other models better suited for this particular dataset..

2.1.1.2. Random Forest:

The Random Forest classifier was employed in the prediction and classification of appropriate crops using several agricultural parameters such as temperature, humidity, soil pH, and rainfall. The data had 2200 records under 22 crop labels with 67% of the data employed for training and the rest for testing.The model attained a 97.32% accuracy, which was a testament to its performance in agricultural classification tasks[5]. The ensemble-based nature of Random Forest enabled better prediction performance through the combination of several decision trees. The research also focused on the significance of feature selection, noting its effect on improving model accuracy when dealing with agricultural datasets.

2.1.1.3. Naïve Bayes:

Naïve Bayes, a supervised learning algorithm that is based on Bayes' Theorem, was employed in this research for crop yield prediction and suggestion by examining the most important soil and environmental parameters. The model takes into account Nitrogen (N), Phosphorous (P), Potassium (K), pH value, Humidity, Temperature, and Rainfall to identify the most appropriate crop to be grown. By determining the probability of each crop being optimal given conditions, Naïve Bayes classifies crops effectively with the assumption of independence between features. The research proved that Naïve Bayes had an accuracy of 99%, thus being one of the best algorithms to use for recommending crops. Its high accuracy is a testament to its effectiveness in dealing with categorical and numerical data, hence being a quick, reliable, and interpretable solution for precision agriculture[6]. The system makes it possible for farmers to make informed decisions, providing greater crop yields and enhanced farm productivity. Future development may include incorporating other environmental factors like seasonal rain patterns and trends in the market to further optimize the recommendation system's accuracy and relevance.

2.1.1.4. Linear Regression:

Linear Regression is a popular supervised learning algorithm used to create a relationship between dependent and independent variables to make precise predictions. Linear Regression is used in this research to forecast crop yield using temperature fluctuations, and farmers can use it to identify the best crops for various climatic conditions. The model examines past data to determine the best temperature range for achieving maximum yield of crops such as wheat, rice, sugarcane, and cotton.Through the use of this method, the system effectively forecasts crop production patterns, indicating that wheat attains optimum yield at 12°C to 22°C and cotton at 25°C to 35°C. The model's success in attaining 90% accuracy points to the high value it offers in facilitating data-driven agricultural planning.In addition, the system suggested here allows for seasonal categorization of crops and advising on optimum planting seasons for various crops[7]. The system can be further improved in the future by incorporating additional environmental factors like soil fertility, precipitation, and market conditions to improve prediction to ensure greater agricultural productivity and profitability for farmers.

2.1.1.5. Weighted K-Nearest Neighbours(K-NN):

Weighted k-NN is an extension of the classic k-NN algorithm in which each of the nearest neighbors is given different weights based on the distance of the neighbors from the query point. Here, weighted k-NN was applied in crop recommendation systems, which is one kind of application used in determining crop suitability under several factors such as moisture levels, temperature, and others on the ground. For example, in a weighted k-NN, if soil moisture is very important, it gives the highest importance to the nearest neighbors that have the most similar moisture levels in the system for determining the best crop for that soil type[8]. It is simple and relatively easy to interpret but tends to fail often on large high-dimensional datasets.

2.1.1.6. Decision Trees:

The Decision Tree algorithm was employed in the research to develop a crop recommendation system that assists farmers in selecting suitable crops based on environmental conditions[9]. Using a dataset containing parameters such as temperature, humidity, rainfall, and soil pH values, the Decision Tree Regressor was implemented with the ID3 algorithm approach. The model achieved 90-92% accuracy by calculating Information Gain and Standard Deviation Reduction to determine optimal splits in the tree structure.

Neural Networks:

Neural Networks (NN) are the computational models where extraordinary precision in analyzing highdimensional and complex datasets has made them some ideal candidate for crop recommendations. In inspiration from biological neural networks of the human brain, these models can identify intricate relationships between variables such as soil moisture, temperature, pH, and crop performance.

Neural Networks are composed of interconnected layers of "neurons" that can process input data, learn relations between the soil condition and optimal crop choice using backpropagation and gradient descent. At each pass through the layers, the network adjusts internal weights to better make predictions of suitable crops. One of the major benefits of using Neural Networks to make crop recommendations is that they capture data patterns which may be nonlinear. For example, the soil moisture content and crop yield are relationship not straightforward, depends on whether the soil is sandy or clayey and by the weather conditions and, sometimes even by the nutrient availability; this kind of things Neural Network can learn over time[10]. Hence, they are bound to outperform more traditional models like decision trees, or k-NNs when the data is extremely complex and noisy

2.1.2. Unsupervised Learning:

Unsupervised learning plays a significant role in agricultural application, particularly in situations where labeled data is scarce. By identifying patterns in large, unlabeled datasets, unsupervised learning can assist farmers in optimizing crop production and resource management. One common application is clustering, where similar data points are grouped based on features like soil properties. This allows farmers to categorize different types of crops or identify regions with comparable soil conditions. Anomaly detection is another use, where unsupervised algorithms identify unusual patterns that may indicate crop diseases or environmental stress, enabling early intervention[11]. Additionally, feature extraction helps uncover hidden factors influencing crop yield or disease prevalence, giving farmers insights into the underlying variables affecting productivity. Data segmentation further aids decision-making by breaking down large datasets into meaningful categories. The process typically begins with collecting large amounts of unlabeled data, such as soil characteristics or environmental conditions. After selecting appropriate models like K-means clustering or principal component analysis (PCA), the algorithms analyze the data to detect patterns without relying on labeled outcomes. The insights gained from these models are then used to make informed decisions about crop rotation, pest control, and resource management, enhancing agricultural efficiency and sustainability.

2.1.3. **Reinforcement Learning**:

Reinforcement learning (RL) is used in crop management to address the challenge of making sequential decisions in uncertain environments, such as weather changes and pest infestations. It allows systems to adapt dynamically by learning from the outcomes of actions, making it ideal for agriculture, where variables like soil conditions, climate, and crop types constantly change[12]. Unlike traditional decisionmaking systems, RL continuously improves its strategy by interacting with the environment. In RL, an agent (e.g., a crop management system) takes actions (e.g., deciding when to irrigate or fertilize) in an environment (the farm), receiving feedback in the form of rewards (e.g., improved crop yield). Over time, the system learns to optimize these actions by maximizing cumulative rewards, such as increasing yield or reduce water wastage. RL also balances exploration and exploitation. It tests new strategies (exploration) while leveraging the most successful past actions (exploitation), allowing it to refine decisions over time. This approach can support decisions on irrigation, fertilization, and pest control, improving efficiency in crop management. Although RL has promising potential, its adoption in real- world agriculture is still limited. Most applications are currently in simulated environments due to the high data and computational costs involved. However, RL offers opportunities for more intelligent, adaptive decision-making systems in farming. The application of RL may also spur development in the precision fertilization strategy. Classical fertilization strategies often depend on a strict calendar and do not consider soil nutrient content at real time or crop conditions. In contrast, RL algorithms can adapt fertilization plans based on feedback from sensors in the soil and crop health data, allowing the release of nutrients precisely when and where they are needed most. This reduces the risk of over- fertilization, which leads to a condition where nutrients end up running into the environment to cause further damage. At the same time, it saves money for the farmer. This means that in the pest control arena, RL optimizes pesticide application both in terms of time and quantity applied by virtue of an interaction based on pest population dynamics, crop vulnerability, among other considerations. It acts to reduce pesticide use, promotes sustainable farming practices, and lowers the environmental impact of agriculture through learning from the outcomes of previous pest control actions.

2.1.4. **Artificial Neural Networks (ANN):**

ANN works by mimicking the way biological neurons process information. It consists of multiple layers: an input layer that receives the soil data, one or more hidden layers that process this data through interconnected neurons, and an output layer that provides predictions such as the best crop for a particular soil type. Artificial Neural Networks (ANN) were applied to predict soil types and suggest crops according to particular soil characteristics[13]. The architecture of the model was made up of several layers in order to extract the nonlinear relations between input features like soil pH, water content, organic content, and gas content. ANN employed a supervised learning paradigm where known input-output pairs were utilized to train the model. It was able to differentiate between very minute variations in soil profiles and effectively pair them with crops that are biologically matched for such soil types. Utilizing activation functions within the hidden layers and softmax on the output layer, the network was able to learn to classify multiple crop types with considerable accuracy. The outcomes illustrated that ANN was able to process the complexity and variability of agrarian data efficiently, providing a smart decision support system for precision agriculture. The research proved that ANN models are extremely flexible with heterogeneous data sets and can be used for site-specific crop planning, which plays a vital role in the enhancement of yield and resource utilization.

Reference [14] aimed at using Artificial Neural Networks to predict crop yield with a specific focus on incorporating the complex relationships between environmental and agronomic parameters. The input attributes were an extensive list including soil nutrient composition (Nitrogen, Phosphorus, Potassium), environmental parameters (temperature, rainfall, humidity), and land parameters. The ANN model handled this high-dimensional input through multiple hidden layers, allowing it to learn complicated, non-linear mappings that relate these variables to crop productivity. Training was done with backpropagation and gradient descent, and performance was checked across multiple epochs with accuracy, loss, and RMSE metrics. The ANN had strong generalization capacity, in that it could accurately predict yields even for heterogeneous crop varieties and different climatic conditions. The research emphasized that conventional models tend to fail to detect latent patterns, while ANN has the capability to learn from data adaptively over time. In the future, the research suggests the use of real-time data streams from IoT sensors and the application of optimization algorithms such as Genetic Algorithm or Particle Swarm Optimization to optimize the network for better performance. The aim is to establish a dynamic real-time yield forecast system that assists in smart agriculture and enhances farmer decision-making using credible data insights.the research also reported some of the difficulties with implementing ANN, such as increased training times, requiring large labeled data, and overfitting risk.

To mitigate these, theresearchers proposed methods such as dropout regularization, early stopping, and cross-validation to enhance the robustness and generalizability of the model.

Author	Algorithm Type	Prediction Target	Environmental Factors Considered	Prediction Accuracy	Real-World Applicability	Potential Improvements
Sk AlZaminur Rahman et al.(2018) [8]	Weighted k-NN, Gaussian SVM, Bagged Trees	Soil classification and crop suggestion based on soil series	Chemical features (pH, salinity, organic matter, potassium), geographical attributes	SVM: 94.95%, k-NN: 92.93%, Bagged Trees: 90.91%	Useful in regions with diverse soil series and land types	Increase dataset size for underrepresented soil series, integrate real-time IoT data
Anguraj et al. (2021) [15]	Random Forest, Naive Bayes	Suitable crop recommendation	Soil moisture, temperature, humidity, pH	96.89%	High: IOT integration with GUI for real-time recommendation	Enhanced data collection from sensors to improve real-time precision
Zeel Doshi, Rashi Agrawal,(2018)[16]	Decision Tree, K-Nearest Neighbor (K-NN), Random Forest, Neural Network	Crop recommendation based on environmental factors and soil characteristics, Rainfall prediction for crop suitability	Temperature,Rainfall, Latitude, longitude, altitude, and distance from the sea, Soil pH, aquifer thickness, topsoil thickness	Decision Tree: 90.20%, K-NN: 89.78%,Random Forest: 90.43%, Neural Network: 91.00%	Designed for farmers to recommend suitable crops based on environmental and geographical factors, Includes map visualization	Future work includes crop rotation prediction and the inclusion of economic indicators (crop demand, supply, prices)
Tanmay Banavlikar, AqsaMahir, Mayuresh Budukh, Soham Dhodapkar(2018) [10]	Neural Networks	Best type of crop to be cultivated based on soil moisture content, humidity, and temperature	Soil moisture content,Humidity ,Temperature	Not explicitly stated	Provides crop recommendations to improve farm productivity, Can be extended for use in irrigation systems	Could be adapted to work with larger datasets, Can integrate irrigation systems with smart sensors to automate watering

Table1: Crop Recommendations driven by soil analysis

2.2. Deep learning:

Deep learning, based on deep neural networks, is a powerful approach for learning complex patterns in large, multi-dimensional datasets, such as satellite images and sensor data in agriculture.

2.2.1. Convolutional Neural Networks:

Recently, research has developed a hybrid model with CNN and LSTM networks for soil nutrient prediction and crop yield estimation [17]. A CNN is a proper tool for analyzing spatial features from aerial or satellite images, making it appropriate for rating conditions in the soil and detecting health in wide coverage areas. An LSTM represents a tool that handles time series well, thus capturing historical weather patterns and measurements of the soil as a means of arriving at the appropriate estimates on soil moisture over time. The integrated model exhibited better performance with 0.85 accuracy and MSE of 0.024, significantly improving the accuracy in the estimation of nutrient values in soil. Deep learning models also enable high-level associations between the properties of the soil, the climate, and crop performance, which enables advanced crop recommendation systems. For instance, they can examine extensive datasets in order to determine the best crops for certain soil moisture levels so that the planting schedule is optimized for maximum yield. In addition, the models are applied in such applications wherein they can learn in a real-time manner using new data to adjust appropriately so as to optimize the use of resources and promote sustainable farming. This overall deep learning approaches in agriculture are a giant step forward and ensure actionable insights that increase productivity while making efficient usage of the other inputs like water and fertilizers. New learning approach for multivariate large data sets like satellite images and sensor data in agriculture could be deep learning based on deep neural networks. The developed technology is highly crucial while solving challenges related to predicting soil moisture and recommending crops. A hybrid approach of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks has been developed to predict the soil nutrient and crop yields [16]. CNNs are particularly good at feature extraction in spatially related regions within aerial or satellite images, where the evaluation of the state of the soil condition or the plant health can also be deduced over large areas. On the other hand, LSTMs work very well in handling time series data capturing the historical pattern of weather and soil measurements over time to predict soil moisture with fair accuracy.These integrated models have yielded better performances with an accuracy of 0.85 and a mean squared error (MSE) of 0.024, thereby enhancing the precision many folds in the prediction of soil nutrients. These deep learning models enable advanced crop recommendation systems through high-level associations established between soil properties, climate conditions, and crop performance. It can obtain much knowledge from these datasets on which crops to plant based on specific levels of soil moisture, thus allowing the maximum yields through optimal planting schedules. Deep learning models can, therefore, adopt changing environmental conditions in real time with their capability for continuous learning. The technology enhances resource efficiency in particular with regards to water and fertilizer management, thus encouraging sustainable farming practices [18]. Overall, deep learning methodologies represent significant advancements deployed in agriculture to provide productive insights toward improving yields without inputs such as water and fertilizers being wasted.

3. Literature review

There are a range of works under discussion here in which researchers investigated various machine learning methods and the extent to which they are accurate in agricultural prediction.

The paper [19] proposes a soil fertility, rainfall, and nutrient level (N, P, K) based crop recommendation system. It compares the machine learning algorithms and found that Self-Organizing Maps (SOM) were superior to K-Means for classifying the soil, whereas JBK yields the maximum accuracy for crop selection. The research also incorporates IoT-based soil monitoring with real-time data acquisition. The methodology is weak in the absence of a yield prediction model, which makes it not as effective in the planning of the whole farm.

The article [20] emphasizes soil classification and crop recommendation with machine learning for improving agricultural productivity. Feature selection is done by a Gradient Boosted Tree (GBT) algorithm, and ten soil types are classified with high accuracy by a Feed Forward Neural Network (FFNN). Soil-Crop Suitability Matrix provides mapping of crops to soil types, enhancing the precision of recommendations. The study compares GBT-FFNN with CNN and Multi-Class SVM and demonstrates that GBT-FFNN is best. Although the system is correct in soil-based crop picking, it fails to forecast crop yield, with room for more advancement.

The paper [21] investigates crop yield forecasting based on past agricultural records, such as temperature, precipitation, and soil nutrients. Some of the machine learning models, including Decision Trees, Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs), are tested, and it is found that Random Forest yields the best accuracy. Feature selection techniques are used to enhance model performance by highlighting key soil and climate factors. Although the study successfully estimates crop yield, it fails to include soil classification for suggesting appropriate crops. This makes it less effective in optimizing agricultural decisions to their fullest potential.

The article [22] investigates Indian agricultural statistics to forecast crop yields based on machine learning. Rainfall, temperature, humidity, soil, and fertilizer usage are among the factors taken into account to construct predictive models. SVM, Decision Trees, Random Forest, and ANN are compared in the research, and the conclusion is that Random Forest provides the best accuracy. Feature selection methods also identify the most contributing factors in estimating yield. But the research only addresses the issue of yield prediction without incorporating soil classification and crop recommendation, which are vital to integrated farm planning.

The article [23] uses a Naïve Bayes classifier to suggest crops as per soil and climate conditions. The system receives inputs such as temperature, humidity, soil moisture, and pH to predict crops. A high volume of data from Kaggle and government data is utilized for training to make accurate predictions. A mobile application allows farmers to input environmental parameters manually or leverage automated location-based data collection. In spite of its success in crop selection, the research does not include yield prediction, which is the key to optimizing agricultural efficiency..

The paper [24] proposes a crop recommendation system based on ML employing ensemble learning with Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random

Tree, and Naïve Bayes. Majority voting scheme is used for the selection of the optimal crop considering soil parameters for enhanced precision. The models SVM and ANN are used as base learners in order to get enhanced system performance across various conditions of soil. Nevertheless, whereas the model works well in suggesting crops, it lacks yield estimation, lowering its overall contribution to agricultural decision-making. Lack of real-time soil monitoring is another handicap.

The research paper [25] suggests an ensemble machine learning-based crop recommendation system to mitigate the inefficiencies of conventional farming practices. It combines Decision Trees, SVM, and Random Forest, applying majority voting for improving prediction accuracy. It shows that ensemble learning enhances the performance of separate models and becomes a superior decision-support tool for farmers. Yet, the model is missing a yield prediction module, which is essential in predicting the levels of production. Moreover, real-time monitoring of the environment is not provided, restricting adaptability to varying conditions.

The paper [26] discusses machine learning-based prediction of crop yields, citing the shortcomings of historical mean-based conventional estimation techniques. It compares Linear Regression, Random Forest, SVM, and ANN and concludes that Random Forest and ANN have the best accuracy. Feature selection methods enhance input parameters by targeting key environmental and soil conditions. Although the research enhances the accuracy of yield prediction to a great extent, it does not include soil classification for choosing crops. The absence of real-time monitoring and adaptive learning also limits the system's capacity to adapt to dynamic environmental conditions.

Paper Title	Work Done	Advancements Over Previous Study	Gaps Identified
Crop Selection Method to Maximize Crop Yield[27]	Introduced a rule-based decision system for crop selection based on soil type, climate, and economic factors.	Shifted from intuition-based farming to data-driven decision-making.	Did not use machine learning; lacked yield prediction models and real-time adaptability.
Implementation of Machine Learning Algorithms for Crop Recommendation Using Precision Agriculture[28]	Applied machine learning (Random Tree, k-NN, Naïve Bayes) for crop recommendation based on soil characteristics.	Improved accuracy using ensemble learning, automating crop selection.	Did not incorporate yield prediction; lacked real-time environmental monitoring.
Comparative Analysis of Machine Learning Algorithms in the Study of Crop and Crop Yield Production[29]	Compared multiple machine learning models (SVM, Decision Tree, Random Forest, k-NN) for crop classification and yield prediction	Introduced yield prediction models, improving productivity estimation.	Did not integrate soil classification into crop recommendations; relied only on historical data.
Crop Yield Prediction Using Deep Reinforcement Learning[30]	Used Deep Reinforcement Learning (DRL) for adaptive yield prediction based on changing environmental factors.	Improved adaptability compared to static ML models.	Did not integrate soil classification; computationally complex and inaccessible for small farmers.
Crop Recommendation System to Maximize Crop Yield in Ramtek Region[31]	Developed a regional crop recommendation system using soil fertility, rainfall, and temperature data.	Used location-specific data for better recommendations.	Limited to a specific region; did not include yield prediction or real-time monitoring.
Crop Prediction Based on Characteristics of the Agricultural Environment Using Various Feature Selection Techniques and Classifiers[32]	Applied feature selection (Boruta, RFE, Modified RFE) and tested multiple ML classifiers for crop prediction.	Optimized input features for improved accuracy.	Did not include real-time monitoring; dataset was region-specific; no yield prediction.
Soil Classification Based on Machine Learning for Crop Suggestion[33]	Used Random Forest, Naïve Bayes, k-NN for soil classification to recommend crops.	Automated soil classification, reducing dependence on agricultural experts.	Did not incorporate yield prediction; ignored climate variations in recommendations.
Crop Classification and Yield Prediction Using Machine Learning[34]	Integrated both crop classification and yield prediction using ensemble models (RF, XGBoost, ANN).	Combined crop classification with yield forecasting, improving productivity estimates.	Did not integrate soil classification; lacked real-time adaptability to environmental conditions.

Table2: Comparative analysis of Existing studies in Crop Recommendation & Yield Prediction

4. RESEARCH GAP:

It suggests a Crop Selection Method (CSM) based on rule-based decisions considering soil type, climate, water availability, and government policies[27]. Although structured, it is non-adaptive and does not offer yield prediction support. [28] improves crop recommendation with ensemble classifiers like Random Tree, k-NN, and Naïve Bayes but is still devoid of yield estimation or responsiveness to real-time environmental fluctuations. [29] proposes yield prediction and compares a number of classifiers and regressors and determines Decision Tree and Random Forest as leading performers. It does not, however, take soil classification into account in the recommendation process. [30] uses Deep Reinforcement Learning (DRL) to provide adaptive yield predictions to varying agricultural conditions but excludes crop recommendation and requires high computational power, which makes it inaccessible to small-scale farmers. [31] enhances region-specific accuracy with the use of local data for the Ramtek region but does not have yield prediction, scalability, and real-time monitoring. [32] enhances input data with feature selection techniques such as Boruta and RFE and enhances prediction efficiency with ensemble techniques but is region-specific and does not include yield estimation. [33] targets soil classification with the help of Random Forest but does so with high accuracy at the cost of yield prediction and climate adaptability. [34] combines crop classification and yield estimation employing ensemble algorithms like Random Forest and XGBoost but does not make crop suggestions directly dependent on soil classification. [35] optimizes crop classification and yield estimation via ensemble learning and feature selection with increased accuracy but without incorporation of soil data and real-time capability.To overcome these constraints, this research suggests an integrated system that unifies soil classification, crop suggestion, and crop yield estimation within a single system. Further, it integrates a 5-day weather forecast module to dynamically respond to short-term climatic fluctuations. This comprehensive and adaptive system is envisioned to enable more accurate and timely farm decisions, hence enhancing the practicability and effectiveness of machine learning in precision agriculture.

5. Proposed Methodology

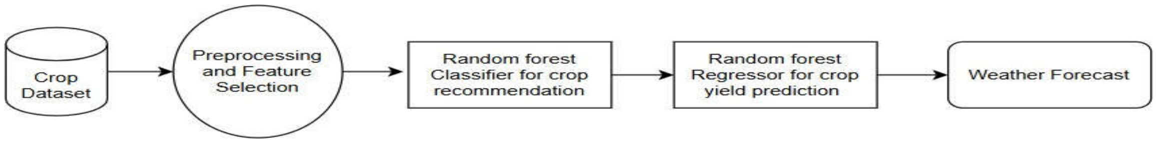

Fig1:Workflow of the Crop Recommendation and Yield Prediction Model

5.1. Data Collection

The foundation of the system relies on collecting high-quality, domain-relevant data. Datasets are compiled from reputable sources such as agricultural research organizations, government databases, and open repositories. This includes details like the soil type (for example, black, red, alluvial, laterite, etc.), which plays a crucial role in determining crop suitability. Instead of gathering raw climatic data, the system relies on user-provided input in the form of the state name. This acts as a proxy for regional climate conditions and agricultural trends. Additionally, users enter the land area they intend to cultivate, measured in square feet, and select the relevant agricultural season, such as Kharif, Rabi, or Zaid. These selections significantly influence the viability of different crops. Historical data on crop yields and regionally cultivated crops further enhances the model's learning capabilities and strengthens its prediction accuracy.

5.2. Preprocessing & Feature Selection

Once the data is collected, it is passed through a structured preprocessing pipeline to ensure it is clean and ready for modeling. This includes addressing missing values, removing duplicate records, and correcting any inconsistencies. Numerical features like area are normalized to ensure uniform scaling, which helps the model learn fairly and efficiently. Categorical variables such as soil type and season are encoded into formats suitable for machine learning algorithms. Feature selection compatibility; the agricultural season, which defines the farming timeline; and the total cultivable area in square feet, which allows for personalized yield calculation. Once these inputs are submitted, the system first utilizes the Random Forest Classifier to suggest the most appropriate crop for the given conditions. techniques are employed to identify the most influential attributes in crop prediction and yield estimation, primarily focusing on the state, soil type, season, and area. This reduces data complexity and improves model performance by eliminating irrelevant or redundant variables.

5.3. Model Implementation using Random Forest

The planned system is designed with a two-stage machine learning architecture. As the first step, a Random Forest Classifier is utilized to suggest the most appropriate crop as a function of environment and geography inputs like State Name, Soil Type, and Season. The ensemble of decision trees in the classifier helps enhance predictability, alleviate variance, and prevent overfitting—optimally suitable to deal with non-linear interactions and high-dimensional categorial data characteristic of agricultural databases.In the second step, a Random Forest Regressor is applied to predict the expected crop yield. The regressor accepts as input the State, Soil Type, Cultivated Area, and predicted crop class probability scores from the first step. By incorporating the crop class probability, the yield estimate becomes better informed and context specific. Random Forest Regressor was selected due to its capacity to learn intricate interactions among features and make accurate, stable predictions even when there is noise and variability in the data.

5.4. Crop Recommendation & Yield Prediction Flow

The user interacts with the system by entering four main
The output of this recommendation is then passed to the Random Forest Regressor, which calculates the expected crop yield. These results are promptly displayed to the user through the web interface, allowing for easy re-entry and experimentation with different scenarios to explore alternative outcomes.

5.5. Web Interface & System Deployment

To ensure accessibility and practical usability, the entire system is deployed as a locally hosted dynamic web application. The user interface includes interactive forms where users can easily select their state, soil type, and season from dropdown menus, and enter the area of land they plan to use. These inputs are seamlessly transferred to the backend machine learning model built with Python, typically managed using a web framework like Flask. Upon submission, the model processes the input values and returns the recommended crop and predicted yield. While the output appears instantly from the user's perspective, it is based on trained predictions derived from integrated learning algorithms. The system is designed to be usable by individuals with little to no technical background, ensuring it serves farmers, agricultural officers, and researchers equally. The interface is lightweight, intuitive, and ensures high responsiveness, even in offline environments.

6. Datset Overview & Analysis:

The data used for this project is agricultural data gathered from various Indian states. The data contains details of different crops cultivated during different seasons and types of soil. Some of the important attributes of the dataset are State_Name, Season, Crop, Soil_type, Area (in square feet), and Production (yield in tonnes). Each record refers to a particular agricultural instance with an Id. State_Name is a field that signifies 29 different Indian states with varying agro-climatic data. The Season column encompasses various growing seasons like Kharif, Rabi, and Whole Year. Major crops like Rice, Wheat, Maize, and Sugarcane are prominently covered. Soil_type is the field that identifies the suitability of crops with the local soil. The dataset overall offers a good base for training a machine learning model for crop recommendation and yield prediction.

6.1. Key Features of Dataset:

Feature Name	**Description**
Id	A unique identifier for each data entry.
State_Name	Name of the state where the crop was cultivated
Season	The agricultural season (e.g., Kharif, Rabi, Whole Year, etc.).
Crop	The type of crop cultivated (e.g., Arecanut, Banana, Dry chillies).
Area	Land area used for cultivation.
Production	Crop yield or production output.
Soil_type	The type of soil in which the crop was cultivated (e.g., Red, Black, Alluvial).

Table 3 : Different Features od dataset

6.2. Dataset Summary:

- **Total Records:** 23,320
- **Unique States:** 29
- **Farming Seasons:** 6 types
- **Crop Types:** 7 major crops
- **Soil Types:** 6 varieties
- **Area Range:** From 1 sqft to 877,029 sqft
- **Production Range:** From 0 to 1,250,800,000 units

7. RESULTS & DISCUSSIONS:

The accuracy of the crop recommendation model was assessed with four classification algorithms: Random Forest, Logistic Regression, Decision Tree, and K-Nearest Neighbors (KNN). The measure of evaluation employed was the overall classification accuracy on a held-out test set.Among all models, the highest accuracy of 94.15% was done by the Random Forest Classifier quite far ahead of other algorithms. Decision Tree Classifier lagged by just 93.59% in accuracy, then KNN by 92.67%, and Logistic Regression had the worst accuracy of 82.87%.These results highlight the benefits of employing ensemble-based models like Random Forest that combine predictions of multiple decision trees to construct a more generalized and resilient model. Decision Tree and KNN were competitive in performance but are less likely to overfit or be sensitive to feature scaling, respectively. Logistic Regression, as a linear model, was unable to discern the intricate, non-linear patterns of the agricultural dataset.The robust and excellent performance of the Random Forest model indicates that it is well-suited for actual crop recommendation tasks, where the data will be noisy, imbalanced, and heterogeneous. Its robustness against overfitting, capability to deal with categorical features, and ability to handle high accuracy make it a suitable choice for decision-making precision agriculture applications.

Model	Accuracy (%)
Random Forest Classifier	94.15
Decision Tree Classifier	93.59
K-Nearest Neighbors	92.67
Logistic Regression	82.87

Table 3: Comparison of Classification Accuracy for Different Machine Learning Models

Feature Importance Analysis

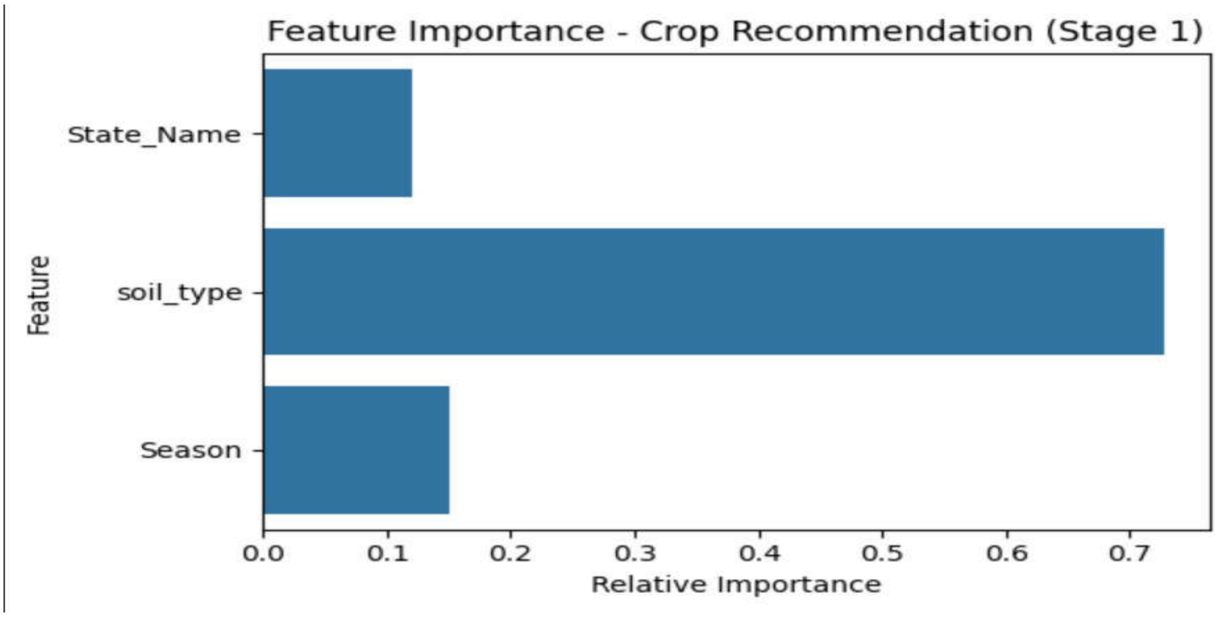

Fig 2: Relative Importance of Input Features in Random Forest-based Crop Recommendation System

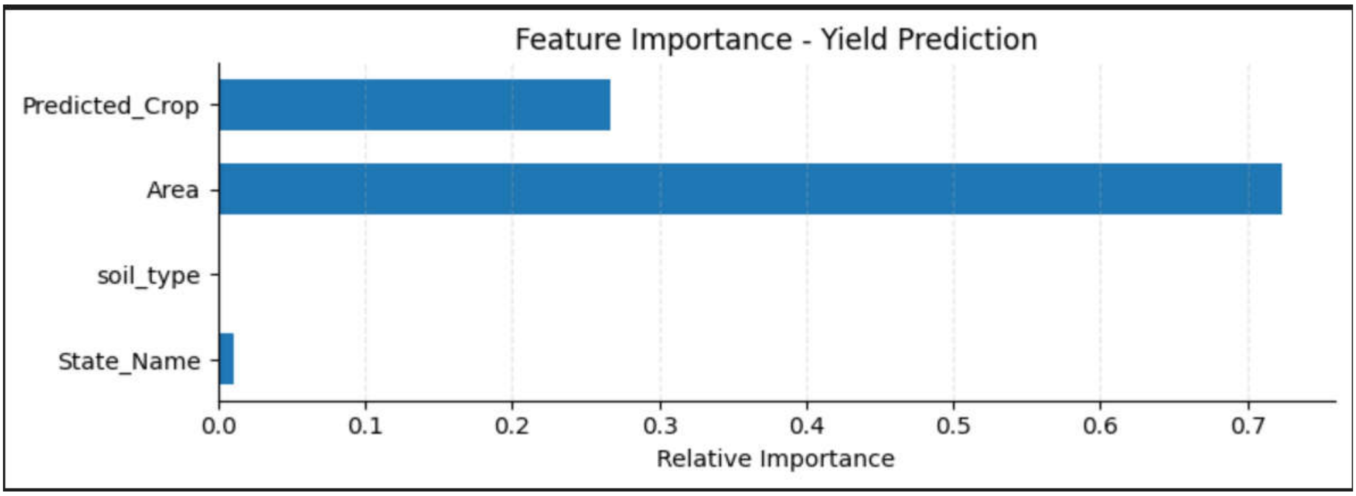

Fig 3: Feature Importance for Crop Yield Prediction using Double Random Forest Model

Distribution of Predominantly Recommended Crops by State

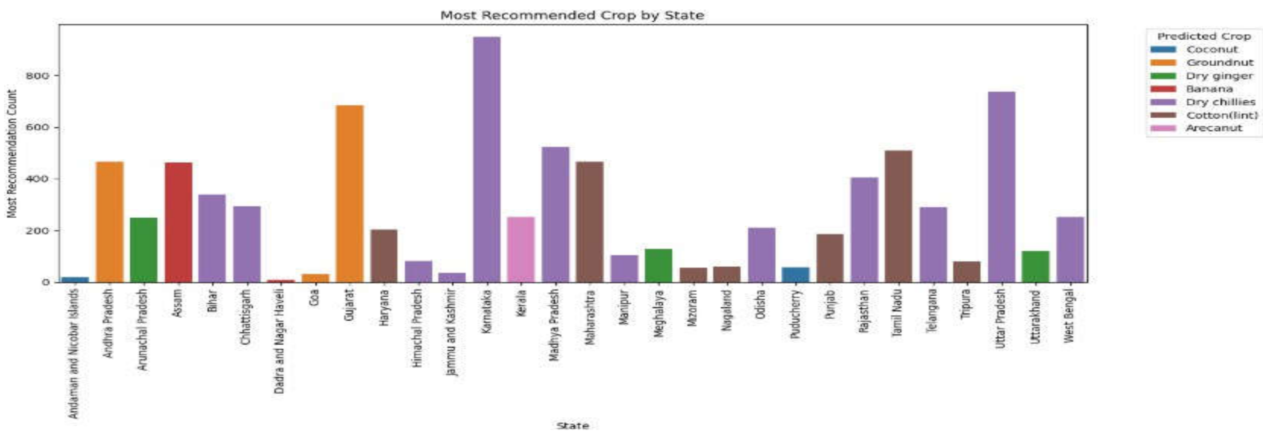

Fig 4: State-wise Dominant Crop Recommendation using DRF Model

Overall Crop Recommendation Trends

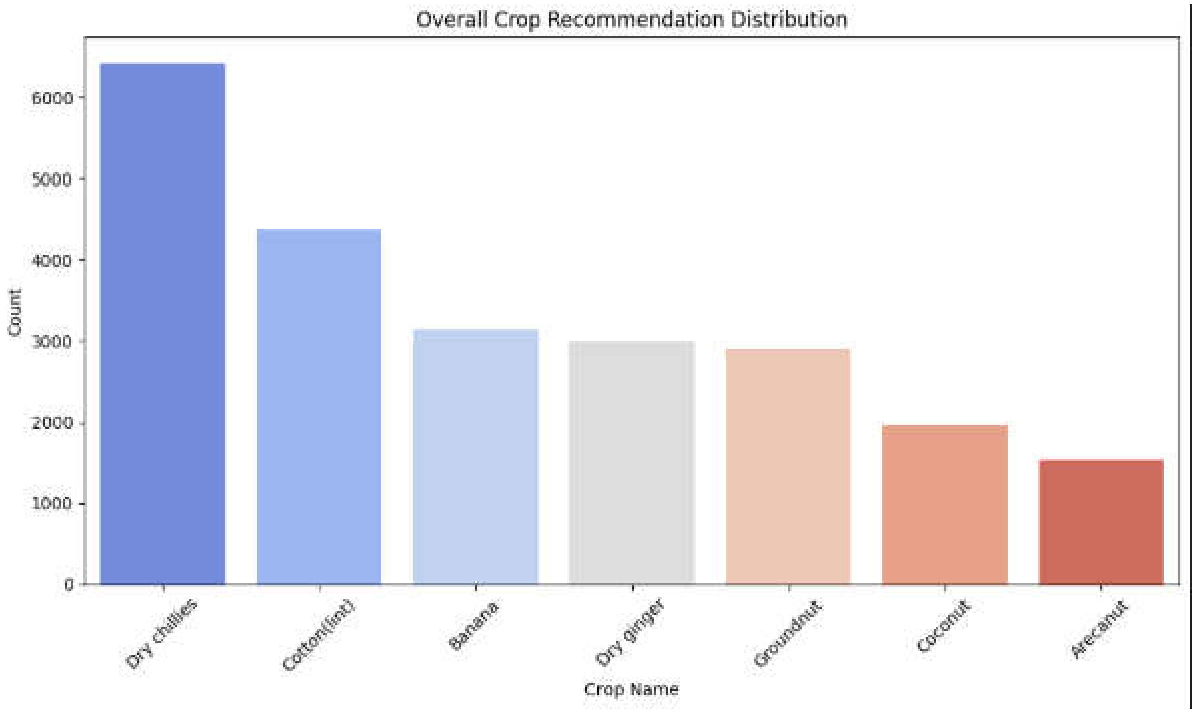

Fig 5: Overall Crop Recommendation Frequency Using Random Forest Classifier

8. CONCLUSION:

An adaptive and integrated agricultural decision-support system has been designed that integrates soil classification, crop suggestion, yield estimation, and 5-day weather forecasting in a single web-based interface. With the Double Random Forest algorithm and a structured data set with historical agricultural data, the system makes accurate predictions of appropriate crops and anticipated yields depending on soil type, region, and seasonal inputs. In contrast to earlier methods that were not fully integrated or flexible, this solution fills major gaps by providing both classification and prediction capabilities within a single platform. The addition of short-term weather forecasting using past data also adds to decision-making by giving a glimpse of future climatic conditions. Overall, the system facilitates precision farming by allowing farmers to make informed, data-driven decisions, resulting in enhanced productivity and sustainable agriculture.

9. FUTURE WORK

While the current system demonstrates high accuracy in crop recommendation and yield prediction using the Double RandomForest algorithm, there are several opportunities for enhancement in future iterations. The current model is trained on historical data and tested on a local server; future versions can be deployed on cloud platforms to allow broader accessibility and scalability for farmers across different regions. Multi-language support and mobile application integration can also improve usability, especially for users in rural and remote areas. Further, incorporating farmer feedback into the model loop could make the system more personalized and context-aware. From a machine learning perspective, experimenting with advanced ensemble methods or deep learning models may uncover additional insights and improve prediction performance. Finally, continuous dataset expansion and periodic model retraining will be necessary to adapt to changing agricultural patterns, emerging crops, and shifting climate conditions, ensuring the tool remains relevant and impactful for long-term agricultural planning.

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